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Manufacturing Capability Assessment for Human-Robot Collaborative Disassembly based on Multi-Data Fusion

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Abstract

In view of the fact that various resources are shared as services globally today in the manufacturing industry, the assessment and optimization for manufacturing capability of human-robot collaborative disassembly is the premise to realize the aggregation and optimization of the disassembly services, and provides the best basis for the optimal scheduling in the workshop. While human are the most basic manufacturing resource and industrial robots (IRs) are the most advanced, we establish a set of complete manufacturing capability assessment system and assessment model for human-robot collaborative disassembly in this paper. For the reason that most of the capability assessment method before ignored the data source selection of the assessment object, only used real-time data or historical data, this paper fuses the historical data and real-time data through manifold algorithm to get more accurate results. On this basis, we assess the manufacturing capability of human, robots, human-robot collaboration using the improved method combining PCA and Grey correlation degree method and AHP in disassembly process. Finally a case study is implemented to demonstrate the feasibility and effectiveness of the proposed method.

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Keywords: Human-robot collaborative disassembly; Manufacturing capability; Assessment; Data fusion

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1. Introduction

Increasing quantity and shorting life of electrical and electronic equipment leads to generation of enormous amount of waste electronic products, which may give rise to an exponential increase in the production of waste, and saturating landfills and some of which contain a multitude of valuable materials such as metal and plastics[1]. Remanufacturing, as the key link of the sustainability development strategy, can extend life cycle of the product and reduce resource consumption and waste generation over entire life cycle[2]. And the performance specifications of reusable components may achieve lower cost or even exceed those of new products from traditional manufacturing because of the adoption of latest technologies[3]. Remanufacturing is achieving growing significance in the worldwide political and research meeting like the 2015 G7 Summit Declaration due to the above features.

A complete remanufacturing chain quintessentially includes disassembly, clearing, re-conditioning and re-assembly stages[4]. And the most critical and time consuming step of remanufacturing is disassembly, and disassembly tasks were traditionally carried out using manual labor[5]. There are a host of problems like low efficiency, high cost, fatigue, hidden danger for human's health when human perform disassembly task. Manufacturing industries are shifting towards automated processes by using robots, and IRs is the perfect option for enhancing production automation, which complements human strengths in manufacturing processes by handing high repeating, position precision, high payload and fatigue[6]. And IRs can increase the mass disassembly. But there is a vital matter that the disassembly quality and flexibility of IRs is not as excellent as human's at present stage of technology because human has stronger learning ability, better strain ability. For example, when dealing with the hazardous material ,such as damaged battery which contains corrosive liquid, IRs is the better choice. When dealing with some fragile parts, like glass screen, human are the better choice. So when a waste phone or laptop is disassembled, human-robot collaborative disassembly is a good option through the complement for manufacturing capability of human and IRs.

The concept of human-robot collaboration was put forward intensely early in manufacturing industry in [7]. On one hand IRs are able to perform more human-like task in disassembly process increasingly, on the other hand the continued presence of human workers allows the system to retain the flexibility level to adapt to new product designs and respond to unexpected event[8]. Human-robot collaborative disassembly can improve disassembly efficiency, ensure the safety of workers and has more flexibility. But there are many challenges for human-robot collaborative disassembly, especially the manufacturing capability assessment for human-robot collaborative disassembly. In information age, the manufacturing capability are circulating in the form of service resource completely[9]. It's crucial to have a comprehensive assessment about the manufacturing capability for human-robot collaborative disassembly to get the basis for schedule in workshop.

For human-robot collaborative disassembly, the previous research on manufacturing capability lacked a set of capability indicators system, and only focused on economic benefits, ignored the social and environment benefits. The assessment methods before only selected real-time data or just historical data， which would be over generalization. This paper establishes a relatively complete manufacturing capability assessment indicator system and assessment models for human-robot collaborative disassembly based on sustainable development; and puts forward an assessment method based on multi-data fusion.

The rest of the paper is organized as follow: the related works is given in section2 and assessment models is given in section 3. Section 4 introduces the algorithm of assessment. And in section 5, we verify the validity and rationality of the assessment method and analysis the results of the experiment. Finally some conclusions are given in section 6.

2. Related works

The concept of manufacturing capability was first put forward by Skinner[10], he proposed that manufacturing capability was composed of cost, quality, time and the relationship among the elements. Later, an ocean of theoretical and empirical studies have found study on it. Luo Y et al. proposed manufacturing capability included design capability, simulation capability, product capability and established a multidimensional information model of manufacturing capability[11]. Liu C et al. thought manufacturing capability was comprised of processing capability and production capability for outstanding decision-making and proposed a model and evaluation method of manufacturing for outstanding decision-making[12]. But the research on manufacturing capability for human-robot collaboration is in an initial stage, and lack of a complete assessment architecture.

Akella P et al. defined the human-robot collaboration in the assembly as "Cobots, a sub-set of IADs, implement software defined virtual guiding surfaces while providing some amplification of human power"[13]. Faber M, Bützler J and Schlick C M analyzed the features of human and IRs, they said robots were good at repetitive and monotonous steps, humans were able to adapt flexibly to new situations and upcoming problems while assembling[14]. Krüger J et al. gave a survey about forms of human-robot collaboration in assembly and available technologies that supported the cooperation[15]. Abdullah N, Jafar F A and Maslan M N compared manual disassembly and semi-automated disassembly through an experiment and semi-automated disassembly took less time[16]. Each robot's manufacturing capability isn't the same due to the time being put into working, and worker's manufacturing capability is also different because of their experience, so we need a systematic method to analyze the manufacturing capability of human and industrial robot and then provide the basis for the collaboration of human and robot.

The famous American scientist Saaty proposed the analytic hierarchy process (AHP). Tsourveloudis N C and Phillis Y A brought fuzzy comprehensive assessment method into manufacturing industry. There are two kinds of assessment methods in general. The first is subjective assessment method, such as AHP and fuzzy comprehensive assessment method; the second is objective assessment method, like data envelopment analysis[17], Entropy-Weight method[18], topsis, Grey relational analysis[19]. Study on the multiple attribute decision problem mainly focused on solving the static decision problem with multiple indicators according to the isolated time points. For the source of the data in the assessment process, most of the assessment methods' data sources are relatively simple, real-time data or just historical data, while there is a lot of knowledge in historical data and real-time data contains the most timely information. Besides, there is much abnormal data due to the sensor's uncertainty and noise in the environment. If only the real-time data is assessed, it would be over generalization.

In summary, there are three weak points for the study on manufacturing capability for human-robot collaborative disassembly. Firstly, lack of a complete assessment system of manufacturing capability for human-robot collaborative disassembly. Secondly, lack of basis for the allocation of disassembly task of human-robot collaboration. Thirdly, the data source of assessment isn't comprehensive. To overcome these limitations,we establish a relatively complete manufacturing capability assessment indicator system in section 3.1 and assessment models for workers and IRs based on sustainable development in section 3.2; and put forward an assessment method based on data fusion. We find the data sources related to the assessment objects' manufacturing capability according to the indicator system in section 3.3; then we fuse the historical data and real-time data to get more accurate data as the input of the assessment method; next, we assess the manufacturing capability of workers and IRs in the disassembly process using the method combining AHP with Grey relational analysis; at last, we rank the objects based on the assessment results of comprehensive capability.

3. Assessment model

3.1. Assessment indicators

We get the manufacturing capability indicators in disassembly process for workers and IRs separately considering the similarities and differences of workers and IRs from economic benefits, environmental benefits and social benefits based on sustainable development in Table 1.

3.2. Assessment model

Taking the computer host as an example, the disassembly tasks can be designed with different sequences, which correspond to different disassenbly stages and data. To avoid the one-sidedness single data source data brings, it can get more accurate assessment data through fusing historical data and real-time data. The problem is abstracted as time, indicator, disassenbly sequence, scheme, the four dimensions decision problem. There are n objects to be assessed, $a_1, a_2, \ldots, a_n$; there are m indicators of p stages of disassembly sequence, x_{ij}, $i=1, 2, \ldots, m; j=1, 2, \ldots, p;$ there are q time segments to form a data column $\{x_{hij}(t_k)\}$, where $h=1, 2, \ldots, n; i=1, 2, \ldots, m; j=1, 2, \ldots, p; k=1, 2, \ldots, q$ in Table 2.

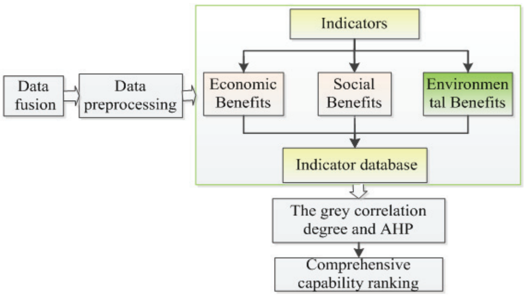

Fig. 1. Assessment model for IRs and human

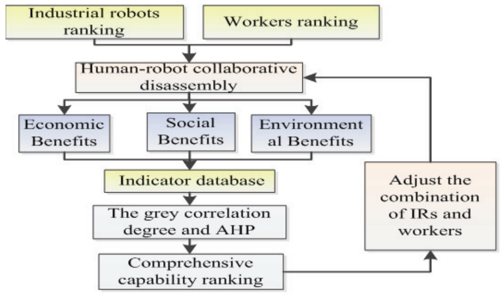

Fig. 2. Assessment model for human-robot collaborative disassembly

This paper establishes manufacturing capability assessment models for human and IRs, human-robot collaborative disassembly based on sustainable development and connotation of manufacturing capability for disassembly in Fig. 1 and Fig. 2. The assessment indicators of human and IRs are summarized from three aspects, that is economic benefits, social benefits and environmental benefits, then the data is collected from the disassembly workshop according to the indicators, and then being processed by data fusion and assessment algorithm in Fig. 1.We can get the remanufacturing capability ranking results of human and IRs by the method mentioned in Fig. 1, then we arrange for humans and IRs to work together according to workshop schedule and the results of assessment in Fig. 2. And the last step involves schedule and optimization in disassembly workshop, assessment work provides basis for the next step.

Table 1. Indicators for manufacturing capability of IRs and human.

Goal		Indicator	Sub-indicators of IRs	Sub-indicators of human
Manufacturing capability assessment for human-robot collaborative disassembly	economic benefits	disassembly quality	degree of partition	
			parts integrity	
			parts demand	
		disassembly cost	equipment depreciation	workers' wages
			maintenance cost	
		disassembly time	disassembly time	
			auxiliary time	rest time
		disassembly flexibility	disassembly flexibility	worker's experience
				worker's proficiency level
	social benefits	social benefits	safety	
			innovative	worker's fatigue degree
	environmental benefits	energy consumption	brake energy consumption	
			bus energy consumption	
			motor energy consumption	
		environmental protection	noise	
			wastes	

Table 2. Time series data table.

Alternatives	Indicator i			
	t_1	t_2	...	t_q
a_1	$x_{1i1}(t_1),x_{1i2}(t_1),\cdots,x_{1ip}(t_1)$	$x_{1i1}(t_2),x_{1i2}(t_2),\cdots,x_{1ip}(t_2)$	...	$x_{1i1}(t_q),x_{1i2}(t_q),\cdots,x_{1ip}(t_q)$
a_2	$x_{2i1}(t_1),x_{2i2}(t_1),\cdots,x_{2ip}(t_1)$	$x_{2i1}(t_2),x_{2i2}(t_2),\cdots,x_{2ip}(t_2)$	...	$x_{2i1}(t_q),x_{2i2}(t_q),\cdots,x_{2ip}(t_q)$
$\vdots$	$\vdots$	$\vdots$	...	$\vdots$
a_n	$x_{ni1}(t_1),x_{ni2}(t_1),\cdots,x_{nip}(t_1)$	$x_{ni1}(t_2),x_{ni2}(t_2),\cdots,x_{nip}(t_2)$	...	$x_{ni1}(t_q),x_{ni2}(t_q),\cdots,x_{nip}(t_q)$

3.3. Data sources of assessment system

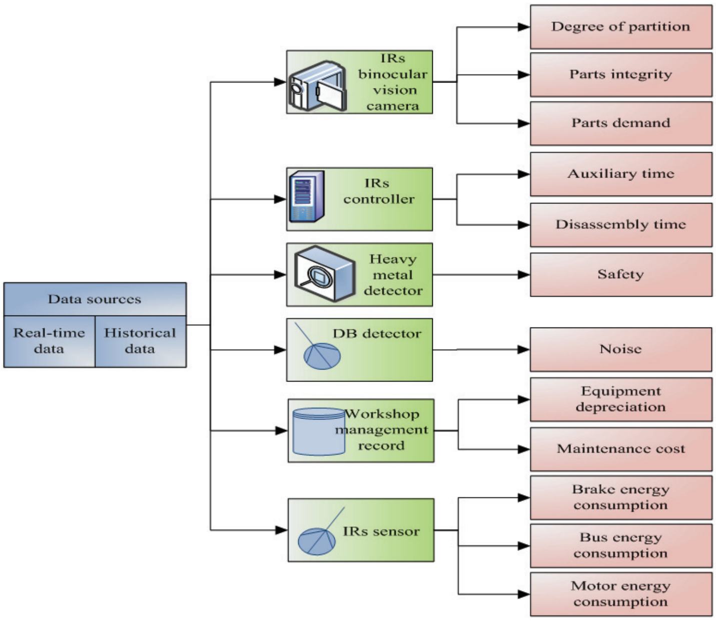

Fig. 3. Data sources of assessment system for human-robot collaborative disassembly.

There are many data sources reflect the manufacturing capability of human and IRs during disassembly process in the workshop. There are many places producing manufacturing data like, controller of industrial robots, sensors, management record and so on in the disassembly workshop. We summarize a slice of data sources based on disassembly indicators in section 3.1 and demonstrate them in Fig. 3. The objective data being assessed comes from this figure.

4. Manufacturing capability assessment based on multi-data fusion

4.1. Data fusion using manifold learning algorithm

Manifold algorithm is a new kind of machine learning method. PCA is one of the most popular manifold algorithms for dimension reduction. The main aim of PCA is to find a set of optimal vector based on liner transformation, and use their liner combination to reconstruct the original sample to minimize the error.

The organization of disassembly data must be poured more attention to when fusing disassembly data. The first step of PCA, constructing the sample matrix of disassembly data for several time periods. For example, on the premise of the same disassembly sequence for all the human and IRs being assessed, we collect $q \times p$ energy consumption values, p is the steps of the disassembly sequence for computer host, q is the number of computer host which is also the time periods being fused.

4.2. Combination of subjective and objective assessment methods

4.2.1. Indicator preprocessed

To ensure the fairness of the assessment, it's indispensable to normalize the indicators. Indicators of benefit type , like quality , safety can be normalized by formula (1). Indicators of cost type, like time, cost, energy consumption and environmental protection can be normalized by formula (2).

$$y_i(k) = \frac{x_i(k) - \min x_i(k)}{\max x(k) - \min x_i(k)} \tag{1}$$

$$y_i(k) = \frac{\max x_i(k) - x_i(k)}{\max x(k) - \min x_i(k)} \tag{2}$$

4.2.2. AHP and grey correlation degree

Different enterprises value different indicators because of its available funds or time or the government's environmental protection policy. AHP can reflect the preferences of decision maker. And gray correlation degree is a subjective assessment method. The two method can complement each other.

1.Get the objective weight through AHP.

Taking the manufacturing capability of IRs as an example, the weight vector of quality, cost, time, flexibility, safety, energy consumption, and environment are $w_q = (w_{q1}, w_{q2}, w_{q3})$, $w_c = (w_{c1}, w_{c2})$, $w_t = (w_{t1}, w_{t2})$, $w_f = (w_{f1})$, $w_s = (w_{s1})$, $w_{ec} = (w_{ec1}, w_{ec2}, w_{ec3})$, $w_{ep} = (w_{ep1}, w_{ep2})$. Calculate the weight the target layer related to the criterion layer, $w_1 = (w_q, w_c, w_t, w_s, w_{ec}, w_{ep})$. We can get the total weight by $w = (w_1^{'}, w_2^{'}, \cdots, w_m^{'}) = (w_q w_{q1}, w_q w_{q2}, \cdots, w_c w_{c1}, w_c w_{c2}, \cdots, w_{ep} w_{ep1}, w_{ep} w_{ep2})$.

2.Determine the optimal indicator sequence x_0

Select the optimal manufacturing capability factors sequence as the reference sequence $x_0 = (x_{01}, x_{02}, \cdots, x_{0\mathrm{m}})$ after data processed, in which $x_{0j} = \max_i \max_j (x_{ij})(i = 1,2,\cdots,n; j = 1,2,\cdots,m)$.

3.Calculate the correlation matrix

The indicators sequence of the object assessed is $x_i = (x_{i1}, x_{i2}, \cdots, x_{in})$, ξ_{ij} is the correlation between the *jth* indicator in x_i and the *jth* in x_0. ξ is the correlation matrix.

$$\xi = \begin{bmatrix} \xi_{11} & \xi_{12} & \cdots & \xi_{1m} \\ \xi_{21} & \xi_{22} & \cdots & \xi_{21} \\ \vdots & \vdots & \vdots & \vdots \\ \xi_{n1} & \xi_{n1} & \cdots & \xi_{nm} \end{bmatrix} \tag{3}$$

$$\xi_{ij} = \frac{\min_i \min_j |\Delta_{ij}| + \rho \max_i \max_j |\Delta_{ij}|}{|\Delta_{ij}| + \rho \max_i \max_j |\Delta_{ij}|} \quad , \quad |\Delta_{ij}| = x_{ij} - x_{oj}\,(i = 1,2,\cdots,n; j = 1,2,\cdots,m). \tag{4}$$

4.Calculate the gray correlation degree of each object assessed

$$R = (r_1, r_2, \cdots, r_n) = \xi * w^T \tag{5}$$

in which $w = (w_1, w_2, \cdots, w_m)$ is the subjective weight in step 1. $r_i = \sum_{j=1}^{m} \xi_{ij} w_j$ is the manufacturing capability value of a_i.

5. Case study and analysis

5.1. Data fusion using manifold algorithm

In order to manifest the effect of data fusion, we take the bus energy consumption value of IRs as an example. The data is organized by one or several cycles of disassembly sequence according to actual situation. The method in section 4.1 can get the principle component from the data of several different time periods. And the other indicator data can be processed in the same way. We take the MATLAB as the experimental tool. The red line is real-time data of bus energy consumption, the black line and green line is historical data of bus energy consumption. The fusion data can keep the features of the original data well in Fig. 4 and save assessment time when there is large scale of data being assessed. And the time results of experiments are put in section 5.3.

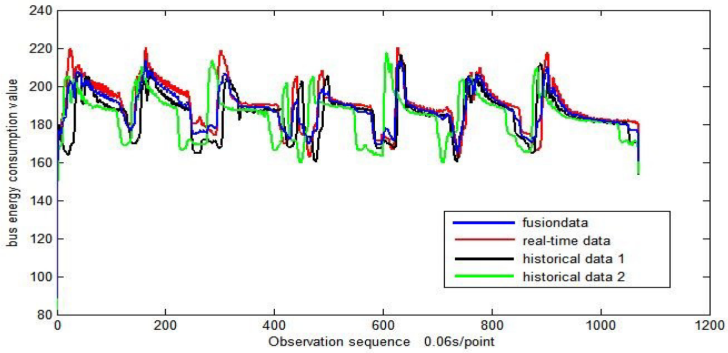

Fig. 4. Trajectory of data fusion through PCA.

5.2. Comprehensive assessment of subjective and objective methods

5.2.1. The assessment data

For structure, we get the data according to the data sources in section 3.3 and reduce some due to the actual situation in the workshop. Then we get the input data of assessment through data fusion.

For IRs, there are economic indicators, like disassembly quality(x_1 degree of partition, x_2 parts integrity, x_3 parts demand), disassembly cost(x_4*/yuan* equipment depreciation, x_5*/yuan* maintenance cost), disassembly time(x_6*/min* disassembly time, x_7*/min* auxiliary time); social indicator,(x_8 safety); environmental indicators, energy consumption (x_9*/kwh* brake energy consumption, x_{10}*/kwh* bus energy consumption, x_{11}*/kwh* motor energy consumption), environment(x_{12}*/db* noise, x_{13}*/kg* waste) in Table 3.

For human, there are economic indicators, like disassembly quality(x_1 degree of partition, x_2 part integrity, x_3 parts demand), disassembly cost(x_4*/yuan* workers' wages), disassembly time(x_5*/min* disassembly time, x_6*/min* rest time); social indicator(x_7 safety); environmental indicators, environment(x_8*/db* noise, x_9*/kg* waste) in Table 4.

Table 3. The values of IRs' indicators.

	quality			cost		time		safety	energy			environment	
	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}
IR1	0.82	0.65	0.84	95.0	9.0	9.9	2.0	9.5	187.8	75.1	52.6	100.0	18.5
IR2	0.75	0.75	0.80	90.4	8.0	10.5	2.0	8.5	169.9	84.9	52.4	77.5	20.0
IR3	0.55	0.30	0.82	78.5	2.0	11.9	1.8	9.5	130.0	72.5	55.0	99.9	31.6
IR4	0.84	0.80	0.82	97.9	7.5	14.9	3.9	8.9	132.4	75.0	57.4	82.6	15.9

Table 4. The values of workers' indicators.

	quality			cost	time		safety	environment	
	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9
worker1	0.89	0.87	0.85	545.1	25.0	9.9	5.0	50.0	9.5
worker2	0.92	0.91	0.81	480.5	31.5	7.0	5.0	48.9	8.5
worker3	0.89	0.89	0.84	509.7	29.5	5.5	4.0	54.9	10.5
worker4	0.88	0.94	0.85	199.9	34.0	6.5	6.0	63.0	12.6

5.2.2. The subjective weight

We get the total weights of IRs and human separately according to our preference through AHP in Table 5 and Table 6. Then process the data through formula (1) and (2).

Table 5. The total weights of IRs.

indicator number	1	2	3	4	5	6	7
weight	0.117	0.091	0.052	0.104	0.026	0.234	0.026
indicator number	8	9	10	11	12	13	
weight	0.14	0.03675	0.03675	0.0315	0.0525	0.0525	

Table 6. The total weights of human.

indicator number	1	2	3	4	5	6	7	8	9
weight	0.135	0.105	0.06	0.2	0.14	0.06	0.2	0.04	0.06

5.2.3. The manufacturing capability ranking of IRs and human in disassembly process

Process the data in Table 3 and Table 4 through formula (1) and (2). Select the optimal indicator sequence, the sequence is (1,1,1,1,1,1,1,1,1,1,1,1,1) for IRs and (1,1,1,1,1,1,1,1,1) for human. Get the correlation matrix through formula (3) and (4). Lastly, get the manufacturing capability ranking of IRs and human separately in Table 7 and Table 8 through formula (5) and the weight in Table 5 and Table 6. There must be a note that the capability value of IRs and human can’t be compared because the indicators and the weights of IRs and human is different.

5.2.4. The manufacturing capability assessment for human-robot collaborative disassembly

The ranking of IRs and human in section 5.2.3 provides a basis for human-robot collaborative disassembly. Accorging to the principle of complementary capability, for example we let IR3 and worker2 work together to improve IR3’s disassembly quality. Than we use the same assessment method to check the results after human-robot collaborative disassembly. The data in Table 9 is the improvement results that human-robot collaborative disassembly compared to IRs alone.

Table 7. Manufacturing capability assessment results of IRs.

	quality	cost	time	safety	energy	environment	comprehensive value
IR1	0.2152	0.0472	0.2419	0.1400	0.0684	0.0573	0.7834
IR2	0.1665	0.0562	0.2600	0.0467	0.0592	0.0871	0.6308
IR3	0.0926	0.13	0.1300	0.1384	0.0890	0.0350	0.6402
IR4	0.2372	0.0473	0.0447	0.0692	0.0707	0.0886	0.5970

Table 8. Manufacturing capability assessment results of workers.

	quality	cost	time	safety	environment	comprehensive value
worker1	0.1449	0.0667	0.1600	0.0990	0.075	0.5456
worker2	0.2113	0.0761	0.0931	0.0990	0.100	0.5796

worker3	0.1445	0.0715	0.1301	0.0667	0.0581	0.4646
worker4	0.1959	0.200	0.0876	0.2000	0.0333	0.7168

Table 9. Improvement of manufacturing capability of human-robot collaborative disassembly.

	quality	cost	time	safety	energy	environment	Comprehensive value
IR1&worker3	33.4%	76.7%	38.5%	-27.6%	151.5%	53.9%	33.8%
IR2&worker4	87.7%	60.3%	-11.2%	-17.3%	45.7%	90.1%	37.7%
IR3&worker2	124%	22.3%	-6.1%	-36.8%	58.9%	65.3%	23.1%
IR4&worker1	22.3%	116%	21.3%	-24.9%	51.1%	40.6%	27.8%

5.3. Results analysis

(1) We give IRs and human different weights according to their different capability features when using AHP. For indicators of quality and safety, We give more weight to human than IRs; for time, we give more weight to IRs than human, because IRs work faster and human work better, we should let them do something they are good at. And we should protect human while there's much danger in the disassembly process.

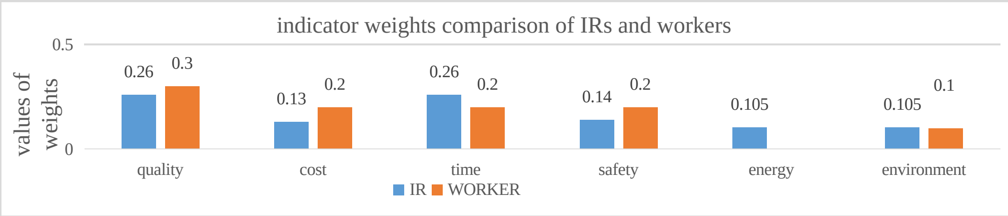

Fig. 5. Indicator weights of IRs and workers.

(2) Comparing to IRs alone, the comprehensive manufacturing capability for human-robot collaborative disassembly is improved much in Table 9. And the improvement results is related to a multitude of factors, like the time IRs and human have worked together and the actual situation of the abandoned products. At the same time, there are quite a few degressive capabilities like safety and time as the cost of improvement. It must be mentioned that the decline in security is relative to IRs. And we can reduce the cost by increasing the privity between IRs and human.

Table 10. Manufacturing capability ranking

Ranking results	
Capability ranking of IRs	IR4<IR2<IR3<IR1
Capability ranking of workers	worker3<worker1<worker2<worker4
Improvement ranking	IR3&worker2<IR4&worker1<IR1&worker3<IR2&worker4

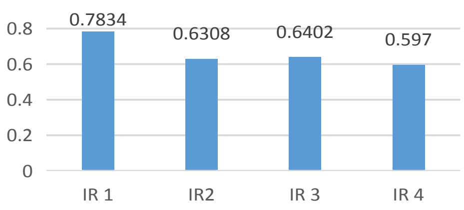

Fig. 6. Comprehensive manufacturing capability of IRs.

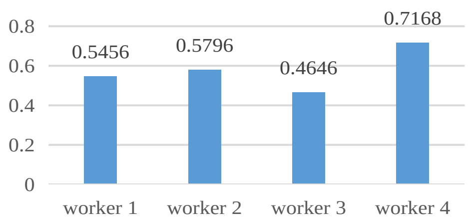

Fig. 7. Comprehensive manufacturing capability of workers.

(3) Manifold algorithm PCA can process data effectively, reduce the assessment time and improve the utilization of data. In the comparing experiment, the assessment time the method in this paper spent is shorter than the traditional assessment method. The simulation tool is MATLAB, and the data amount is 3210*13*4 from four IRs.

Table 11. Convergence time.

Method	Average time
PCA+AHP+GRAY	8.586s
AHP+GRAY	9.408s
improvement	8.7%

6. Conclusion

Remanufacturing is inline with the direction of sustainable development. Human-robot collaborative disassembly will have a broad prospects in manufacturing industry. Human-robot collaborative disassembly not only can improve the disassembly efficiency and disassembly quality, but also can reduce the fatigue degree of human and ensure human's safety. So this paper provides basis for human-robot collaborative disassembly by establishing a set of manufacturing capability indicators and assessment model based on sustainable development and assessing their own manufacturing capability in the disassembly process. And the assessment method can reduce assessment time in this paper. And we verity the advantages of human-robot collaborative disassembly and the validity of the method through an example.

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